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Turbulent Diffusion behind Vehicles
Experiments and Verification of Roadway Models

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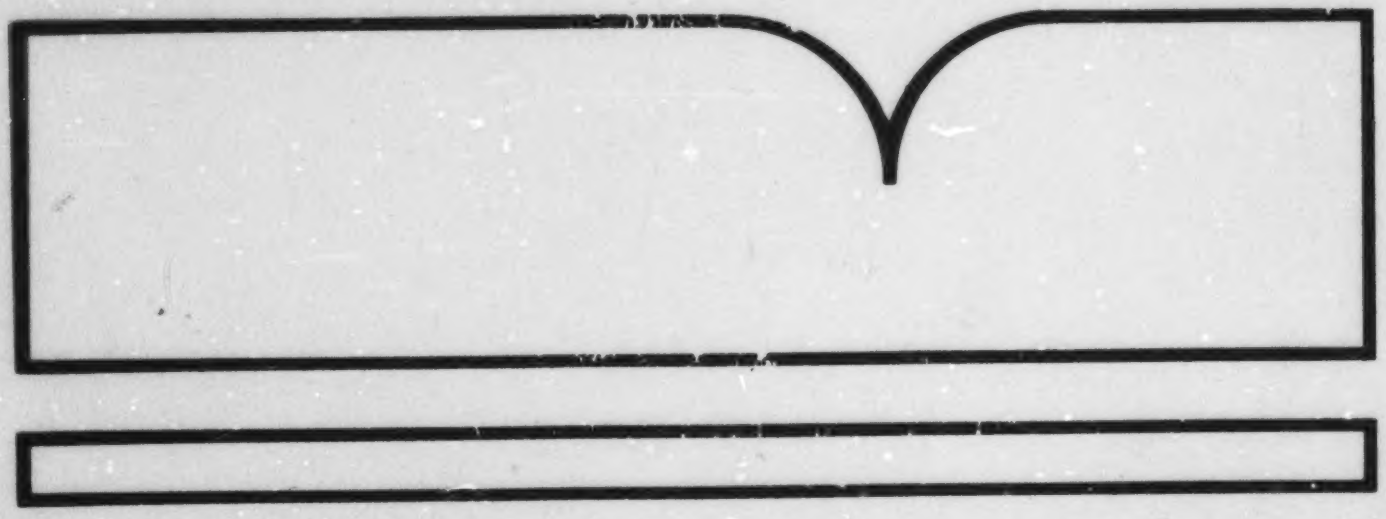

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Turbulent Diffusion Behind Vehicles: Experiments and verification of roadway models

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16. ABSTRACT

Tracer gas was released behind model vehicles in a moving floor wind tunnel and sampled extensively at various downwind distances. A numerical model was used to test various expressions for the eddy diffusion coefficients. The best formulation has been incorporated into the ROADWAY model and it is shown that the current version of the ROADWAY model is an improvement over the earlier version. The predictions of ROADWAY, CALINE3 and HIWAY-2 are compared with the GM Sulfate Dispersion Experiment. It is shown that all three models simulate the GM data very well.

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1. INTRODUCTION

It is now known that turbulent mixing near highways is dominated by vehicle turbulence. Various empirical approaches have been taken to parameterize the effects of vehicle induced turbulence, but until recently there did not exist a theoretical description of vehicle wakes. Eskridge and Hunt(1) derived equations which describe the velocity deficit and they estimated the turbulence by assuming that the turbulence scale lengths were the same as the velocity scale lengths. Wind tunnel experiments by Eskridge and Thompson(2) verified the theoretical description of the velocity deficit, but it was found that the turbulence scales are different from the velocity scales.

The theoretical description of the velocity deficit was modified by Eskridge and Thompson(2), but the strong shear near the surface was not explained completely by the theory. Eskridge and Rao(3) fitted a curve to wind tunnel data to better simulate the vertical variation of velocity near the surface. A summmary of the theory used in the ROADWAY model(4) is given in (3).

Pollutant diffusion in the ROADWAY model was assumed to be describable by using eddy diffusion coefficients which were given by

$$K_i = \left(\overline{u_i'^2}\right)^{1/2} \cdot h, \qquad (1)$$

where h is the vehicle height.

In order to test this hypothesis and several other scale lengths a series of wind tunnel experiments have been conducted using a tracer gas. The techniques used in these wind tunnel tracer experiments are given in Section 2.

In order to determine eddy diffusion coefficients which describe the diffusion in the wake region, a numerical model based upon the vehicle wake theory (described in (3)) is used to simulate the wind tunnel tracer studies. The results are given in Section 3 and the model results of the current version of ROADWAY are compared to the initial version .

A detailed statistical analysis of the performance of ROADWAY, HIWAY-2(5), and CALINE3(6) is given in Section 4. This analysis

shows that there is a range of uncertainty in the observations of about 30% which should be taken into account in model verification studies. The statistical analysis shows that all three models simulate the GM experimental data (7) quite well.

2. TRACER EXPERIMENTS

2.1 The wind tunnel

A wind tunnel was constructed especially for the vehicle studies. A commerically available conveyor belt assembly was used for the test section floor and supporting framework for the entrance, test and exit sections of the wind tunnel. The test section was 4.75 m long with a cross section 0.82 m wide and 0.71 m high.

The entrance section had the same cross section dimensions as the test section. A bellmouth around the perimeter of the entrance directed room air into a section of Verticel (Verticel Co., paper triangular-cell honeycomb; cell length = 0.15 m and hydraulic diameter of 0.01 m). Two fiberglass screens (16 by 18 mesh) were placed downwind of the honeycomb to further lower the freestream turbulence.

The moving portion of the test-section was the rubber conveyor belt. A notched overlapped joint and large end rollers produced a smoothly running belt. Rails along the tops of the walls were installed to support an instrument-traversing mechanism. The longitudinal positions of a probe was set manually vertical and lateral positions were remotely set and read from an operators desk.

The exit section contained a section of Verticel and a lateral contraction to a 0.71 m wide by 0.71 m high cross section. A cast aluminum fan with three blades (diameter of 0.61 m) was powered by a two-speed (1140/1725 rpm), 250 W electric motor. The fan was mounted in a metal shroud for effecient operation. The operating speed of the tunnel during all experiments was 1.9 m/s. The background turbulence intensity was less than 1%.

Homogeneity of the mean flow was checked with the tunnel

operating at test conditions by measuring vertical profiles of velocity at various positions in the test section.

2.2 Model vehicles and instrumentation

Simple block-shaped models were constructed of wood; they had proportions of height, width and length of a typical automobile. Each model was mounted on a baseplate with wheels and rubber tires. Approximate scale ratios of 1/32 and 1/8 were used.

The 1/32 scale block-shaped vehicle was patterned on the dimensions of an intermediate size American automobile: height = 0.043 m, width = 0.055 m, length = 0.145 m, ground clearance = 0.009 m and wheel diameter = 0.024 m.

Concentration measurements were obtained by introducing a passive hydrocarbon tracer gas into the wake of the vehicle and measuring downstream concentrations with a hydrocarbon analyzer. Ethylene gas was used as the tracer as its density is very near that of air, hence simulating a neutrally buoyant effluent source. The tracer was injected into the vehicle wake through a porous "air stone" of the type commercially available for aquarium aeration. This assured that the tracer was injected with minimal momentum in any given direction thus limiting any effects due to jetting of the effluent. The tracer flow rate was held constant during all tests and was continuously monitored using a Meriam laminar flow element in conjuction with a water manometer. A Beckman 400 hydrocarbon analyzer (flame ionization detector) was used to measure the tracer concentration downstream of the model. The analyzer was calibrated using hydrocarbon-free air to set zero scale, and 6760 ppmv ehtylene standard gas to set full scale. The analyzer was shown, in a separate series of tests, to respond linearly to ethylene concentration over four decades of dilution. Samples were continuously withdrawn through a 0.16 cm diameter sample probe at a rate of 200 ccm/min. The instrument output, an analog voltage, was sampled, digitized, and recorded by a minicomputer system using a twelve-bit analog-to-digital converter. An averaging time of 30 seconds was found to yield reasonably stable average values. Background hydrocarbon concentration was sampled both before and after each series of measurements and was subtracted from the measured concentrations.

2.3 Wind tunnel tracer experiments

Lateral profiles of tracer gas concentrations were taken at heights of 0.25h, 0.50h, ..., 3.00h (h is the vehicle height) at distances of x = 30h and x = 60h downstream of the vehicle. The spacing in the lateral direction was 0.18Wd (Wd is the vehicle width). These data were fitted by a least-squares orthogonal polynomial in order to later specify the concentration values on a grid. The data taken at x = 30h was used as inflow boundary conditions and model predictions were compared to the data taken at x = 60h.

3. SIMULATION OF THE TRACER EXPERIMENTS

There is no direct method of extracting a turbulence length from the concentration data which would yield a "best" formulation for the eddy diffusion coefficients. The alternate is to solve the applicable equations and boundary conditions by numerical methods. A numerical simulation is made with the candidates for the turbulent length scale, and model predictions are compared to the wind tunnel measurements.

The numerical model consists of a diffusion equation and the vehicle wake theory described in (3). The data taken at x = 30h in the wind tunnel is used to specify the concentration values on the inflow boundary. The model computations made at x = 60h are then compared to the wind tunnel measurements made at the equivalent downwind position.

The conservation of mass equation for tracer gas in the wind tunnel can be written in a non-dimensional form as

$$\frac{\partial C}{\partial t} + \frac{\partial uC}{\partial x} = \lambda_x h \frac{\partial}{\partial x}\left(K_x \frac{\partial C}{\partial x}\right) + \lambda_y h \frac{\partial}{\partial y}\left(K_y \frac{\partial C}{\partial y}\right) + \lambda_z h \frac{\partial}{\partial z}\left(K_z \frac{\partial C}{\partial z}\right), \qquad (2)$$

where u is the wind speed in the tunnel as determined by the wake theory and the eddy diffusion coefficients have the form

$$\tilde{K}_x = u_\infty \lambda_x K_x, \quad \tilde{K}_y = u_\infty \lambda_y K_y, \quad \tilde{K}_z = u_\infty \lambda_z K_z. \qquad (3)$$

Equation (2) was solved by the same numerical techniques used in the ROADWAY model and these are described in (4). The equation is solved by finite-differences on a 20 by 51 by 16 grid, where Dx = 1.875h, Dy = 0.182Wd and Dz = 0.25h. Examination of the literature suggests a number of candidates for the turbulent length scale, λ_i, and these are given in Table 1.

The model results for each turbulent length scale were compared pairwise with the wind tunnel experiments and a limited number of statistical parameters were determined (Table 2). The results shown in Table 2 imply that the model was insensitive to the horizontal length scale as varying 'λ_x' and 'λ_y' between Wd and h had very little effect on the results. The effect of the vertical scale length was much more apparent as setting 'λ_z' = z resulted in a much better agreement in terms of the rms error and the integrated observed-minus-predicted value. Hence, the eddy diffusion coefficients in ROADWAY are now given by

$$K_x = \sigma_u \cdot W_d \,, \qquad K_y = \sigma_v \cdot W_d \,, \qquad K_z = \sigma_w \cdot z \,, \tag{4}$$

where sigu, sigv, and sigw are predicted by the vehicle wake theory.

The ROADWAY model assumes that averaged wind speed and direction are being used as input. The model does not attempt to incorporate wind direction variation which is important when the mean wind direction is approximately parallel to the road. Under these conditions one expects the model to overpredict pollutant concentrations since wind meander is very important.

The current version of ROADWAY is completely independent of the GM Sulfate experiment data, as compared to the 1979 version (4) which used the GM data to determine five coefficients needed in the wake theory. These coefficients have been determined in the wind tunnel studies of Eskridge and Thompson(2). Table 3 shows a comparision of the two versions of the model. The model results are comparable except that the correlation has improved and the slope of the least-squares linear fit has increased. The increase in slope is actually an improvement as the model should overpredict when the wind direction is within 30 degrees of the orientation of the road. Under parallel wind directions wind meander is important and, as pointed out earlier, the model does

not account for meander.

The conclusion to be drawn from Table 3 is that the modifications to the wake theory made in (2,3) and those reported here have improved the model from its initial version.

4. VERIFICATION AND COMPARISON OF HIGHWAY MODELS

In this section the performance characteristics of three diffusion models, HIWAY-2, CALINE3, and ROADWAY will be determined using the data from the General Motors Sulfate Dispersion Experiment. It should be borne in mind that HIWAY-2 and CALINE3 are expected to perform well when tested against the data from which they were developed. The physics of the problem is handled differently in all three of these models. Intercomparison of model results determine each model's simulation capability as a function of different treatments of modeling of pollutant transport and diffusion.

Two techniques are used to compare the predicted and measured concentrations, namely paired and unpaired comparisions. A paired analysis allows a direct comparison of individual predictions with measured values; while, unpaired techniques determine model behavior on a statistical basis without regard to the spatial and temporal correspondence between measured and predicted concentrations. The techniques used in both the paired and unpaired analysis are described in appendix A.

The results from the paired analyzes are summarized in Table 4. HIWAY-2 and ROADWAY explain about 70% and 65% of the variance, respectively. The slopes of the regression lines are close to unity with small intercept values for all three models. The average errors between predictions and measurements are similar for ROADWAY and HIWAY-2, although the simulation of HIWAY-2 is slightly better than that of ROADWAY. Particularly noteworthy is the fact that the errors of all three models are mostly of an unsystematic nature. This indicates that these models are as good as they can be. The fact that similar results are found for both HIWAY-2 and ROADWAY is indicative of the appropriateness of the methodologies utilized in those models even though they are based on completely different treatments of the physics of the problem. The ROADWAY model uses the vehicle wake theory while HIWAY-2 uses simple parameterizations of traffic-induced turbulence from a

Gaussian approach to handle the transport and diffusion of pollutants near roadways.

In the following analysis it is recognized that the observations include measurement error as well as the variability due to the stochastic or random nature of the atmosphere. It is imperative that this natural variability be taken into account in model evaluation. It should be recognized that there is no significant difference between model predictions and observations as long as the predictions are contained within the natural variability of the observed concentrations. Assuming that the concentrations are directly proportional to the emission strength and indirectly proportional to the wind speed, the variability in the normalized concentration CU/Q (where C is the tracer gas concentration, U is the wind speed and Q is the emission strength) is determined using the General Motors data at the nearest roadside ground level receptor under the nearly perpendicular wind-road orientations. Since the previous investigations (3,4,2) on the role of traffic-induced turbulence suggested the concentrations immediately adjacent to the roadway in the downwind direction are independent of the atmospheric stability and that pollutant diffusion is dictated by the locally generated turbulence, it is appropriate to combine all data from the nearest roadside ground level (0.5 m height) monitor in the downwind direction to investigate the natural variability of the atmosphere. Furthermore, the data are restricted to the cases with wind direction perpendicular to the roadway, since then the transport and diffusion from the source to the receptor are well defined. Also the design of the General Motors experiment ensures that the mechanical turbulence generated by the moving vehicles will be approximately the same for all tracer experiments, because of constant vehicle speed as well as spacing of vehicle packs. Thus, the analysis of the normalized concentration CU/Q for all perpendicular wind-road orientation cases allow the determination of the magnitude of the atmosphere variability (stochastic process).

The cumulative probability plot of normalized concentration, shown in Fig. 1, suggests that the data are normally distributed. The computed mean for CU/Q, the standard deviation of CU/Q, and the coefficient of variation (ratio of the standard deviation to the mean) about the mean are 0.587, 0.154, and 26%, respectively. Thus, the mean for this sample can be reported as $= 0.587 \pm 0.154$. This indicates that the best guess of the unknown true value 'ρ' is $\hat{\rho} = 0.587$ with an expected root mean square error of 0.154 for $(\rho - \hat{\rho})$. If $(\rho - \hat{\rho})$ has roughly a normal distribution (this may always be the case for large data sets), then the accuracy statement can be interpreted as PROB ($\rho \in$ [0.587 -

0.154,0.587 + 0.154]) = 0.68. The above statement is based upon the fact that a normal distribution implies that 68% of the data are within one standard deviation of the mean. The accuracy of the estimated mean value can be assessed using the bootstrap method which is as follows:

a.) Let $\hat{F}$ be the set of the observed data points (18 in this analysis).

b.) Use a random number generator to draw a set of 18 points independently from F, so that each member of the set is an independent random selection of one of the 18 original data points. This new data set, called the bootstrap sample, is a subset of the original set which is plotted in Fig. 1. Some of the original points will have been selected zero times, some once, some twice, etc.

c.) Compute the mean ($\hat{\beta}^*$), the standard deviation ($\hat{\sigma}^*$), and the coefficient of variation ($\hat{\beta}^*$) of the bootstrap set.

d.) Repeat steps (b) and (c) above, a large number of times, say N (N = 1000 here), each time using an independent set of new random numbers to generate the bootstrap set. Denote the resulting sequence of bootstrap means by $\hat{\beta}^{*1}, \hat{\beta}^{*2}, \cdots, \hat{\beta}^{*N}$.

e.) Construct a histogram plot of $(\hat{\beta}^{*1} - \hat{\beta})$, $(\hat{\beta}^{*2} - \hat{\beta})$, ..., based on the N bootstrap sets (called replications).

The histogram of the 1000 bootstrap replications of the mean of the sample, the standard deviation, and the coefficient of variation are plotted in Fig. 2. A normal shaped distribution is found for each parameter suggesting that the original estimate (see Fig. 1) based on standard methods is quite reasonable. The coefficient of variation from the bootstrap replications indicates it could vary as much as 5% from the estimate based on the original sample (26%). Thus, the overall variation in the original sample will be approximately 30%. This limit of plus or minus 30% of the observed normalized concentrations represents the natural variability and should be taken into account in model evaluation studies. Fig. 3 shows a scatter plot of observed concentrations, under near perpendicular cases for the GM data, and the predicted concentrations from the HIWAY-2, CALINE3 and ROADWAY models for the data set used in the bootstrap analysis. A perfect diffusion model under these conditions can perform no

better than the natural variability. From the scatter plot, it is evident that most of the data points from the three models are within the natural variability. Given that the models cannot be expected to perform better than plus or minus 30% of the observed concentrations, Table 5 shows how each model performed with the GM data in predicting the maximum concentrations for each tracer experiment as well as for the entire downwind data set. Again, it is worth noting the similarity of performance of the HIWAY-2 and ROADWAY models in predicting the maximum concentrations. When the entire data set is considered, all models perform about the same. Included in Table 5 are the results from the HIWAY model to facilitate a comparison among the models and to identify the improvement over the earlier version of the HIWAY model.

While the three models perform well in terms of the GM data base as a whole, their ability to predict high concentrations has not been determined. To evaluate the simulation capability of the models in predicting the maximum concentrations the asymoptic extreme value theory will be used. In this method the maximum observed and predicted concentrations in each tracer experiment are rank-ordered and the cumulative probabilities are determined as

$$PROB(X \leq X_1) = EXP[-EXP(-y)], \qquad (5)$$

where $y = (X - u)/a$.

The maxima of the observations and predictions for each GM experiment for the HIWAY-2 model are plotted as a function of the reduced variate, y, The return period is defined as $R = 1/(1-P)$, where P is the cumulative probability. The value of the return period is interpreted as the sample size of additional observations or experiments required to have a 50% chance of observing another value equal to or larger than the value of X of interest. The 95% confidence interval along with the best fit line, which is determined by the method of maximum likehood estimation (MLE), is drawn through the model predicted maximum concentrations. The maximum observed concentrations are also plotted to provide a comparison between the observations and model predictions. The measured data above the mode fall within the confidence band for the model predicted values, which inicates that the model simulates the physical processes leading to the maximum concentrations quite well(plot not shown). The extreme

value distribution for the CALINE3 and ROADWAY model predictions were also compared with the measurements. Again good agreement was found between the predictions and observations as far as the extremes of the maxima (upper tail of the extreme value distribution) are concerned. The statistical parameters for the extreme value distributions from all the three models are presented in Table 6. The second highest of the observed maximum concentration is well within the predicted second highest concentrations indicating that all these models are capable of simulating the atmospheric processes quite well.

Although the results presented above do suggest that the Type I (double exponential) asymptotic extreme value distribution is acceptable, it is useful if a nonparametric analysis approach is utilized to quantify the model performance in simulating the maximum concentrations. In this regard, the boostrap method is applied to compare the cumulative distributions of model-based and monitor-based design values (which is second highest of the maximum concentrations). From the cumulative distributions of these design concentrations based on 1000 bootstrap replications presented in Fig. 4, it is evident that all of the models predict slighly larger values of the concentration than that measured for a given probability. The ROADWAY model provides a more conservative estimate of the design concentration than the other models. At 50% probability, the observed data indicate that the second highest of the maximum concentration is 3.62 ppb, while for the ROADWAY model it is 4.58 ppb. Given that there is no significant difference between model predictions and measurements as long as the predictions are contained within plus or minus 30% of the measured concentrations the above result indicates that the predictions from the ROADWAY model as well as the other two models are in agreement with the measurements. Thus, these models are seen to provide slightly conservative and realistic estimates of the design concentrations. Not only the central tendencies but also the extreme values produced by these models are observed to be in good agreement with the measured data.

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APPENDIX A

In this appendix the standard statistical tests will be summarized for both paired and unpaired tests.

I. Paired comparisons

The following measures of differences between model predictions and measurements were specifically recommended at the Woods Hole EPA/AMS (9) workshop for assessing the model performance.

a. Mean difference between predicted and measured values, given as

$$\bar{d} = \frac{1}{N}\sum_{1}^{N}(P_i - M_i) = \frac{1}{N}\sum_{1}^{N} d_i = \bar{P} - \bar{M} \ ,$$

where Pi and Mi are the predicted and corresponding measured value at the i-th hour, the overbar indicates the mean of the the variable, and N is the sample size. This measure of difference indicates the overall bias of the model in predicting pollutant levels. The bias is the first moment of the distribution of differences.

b. Variance of the difference is computed as

$$S_d^2 = \frac{1}{N-1}\sum_1^N (d_i - \bar{d})^2 .$$

This measure indicates the noise in the data, and is the second moment of the distribution of differences. The square root of the variance is the standard deviation.

c. The root mean square of the difference, given by

$$RMSE_d = \left[\frac{1}{N}\sum_1^N d_i^2\right]^{1/2} = \left[\frac{N-1}{N} S_d^2 + \bar{d}^2\right]^{1/2}.$$

This parameter indicates the actual size of the error produced by the model.

d. Average absolute gross error of the concentration difference evaluated by

$$|\bar{d}| = \frac{1}{N}\sum_1^N |d_i|$$

This parameter is more robust (that is less affected by removal of outliers) than the root mean square error(RMSE).

For normally distributed variables, the bias has a normal distribution, while the variance S_d^2 has a chi-square distribution. The mean square error has a compound distribution. If the distribution of predicted concentrations was the same as the distribution of measured values, then the differences could reasonably be assumed to be normally distributed with a zero mean and a constant variance.

e. Unsystematic and systematic mean square error (MSE) computed

as

$$MSE_u = \frac{1}{N}\sum_{1}^{N}(P_i - \hat{P}_i)^2,$$

$$MSE_s = \frac{1}{N}\sum_{1}^{N}(\hat{P}_i - M_i)^2,$$

where $\hat{P}$ is derived from the relation $\hat{P} = a + bMi$, a is the intercept and b is the slope of the regression line and MSE = MSEu + MSEs.

The importance of these measures is that they will illuminate the sources or types of errors, which can be of considerable help in refining a model (10). When MSEs and MSEu are not computed and MSE is entirely systematic but acceptable, an investigator may be tempted to accept the model as is, because MSE is assumed to be unsystematic. IN such cases, however, further refinement is called for as MSE should be minimized in order that the model is predicting at its maximum possible accuracy. On the other hand if MSE is entirely, or largely composed of MSEu the model is as good as it can be without major reworking.

f. The index of agreement, D, reflects the degree to which the observed variate is accurately estimated by the simulate variate. This is not a measure of correlation or association in the formal sense, but rather a measure of the degree to which model predictions are free of error. At the same time it is a standardized measure so that cross-comparisons of its magnitude for different models can be made. The index of Agreement is given by

$$D = 1 - \frac{\sum_{1}^{N}(P_i - M_i)^2}{\sum_{1}^{N}(|P_i'| + |M_i'|)^2},$$

where $P_i' = P_i - \bar{M}$, and $M_i' = M_i - \bar{M}$.

The variable D specifies the degree to which the observed deviations about $\bar{M}$ correspond in magnitude and sign to the predicted deviations from $\bar{M}$. It is assumed that the portions of the magnitudes of Pi and Mi that are equavilent to $\bar{M}$ are not in error since $\bar{M}$ is considered to be free of error. All the potential for error is assumed to be contained in P_i' and M_i' or in the distances from each Pi to each Mi. Unlike r, the correlation

coefficient, D is sensitive to differences between the measured and predicted means as well as to certain changes in proportionality.

h. The mean fractional error is computed by

$$MFE = \frac{2^{1/2}}{N} \sum_{1}^{N} \frac{(M_i - P_i)}{(M_i + P_i)^{1/2}} ,$$

which is used to determine the model's overall bias to underpredict or overpredict the pollutant concentrations.

II. Unpaired comparisions

In this type of analysis the measured and predicted concentrations are not treated as pairs but are treated as separate data sets. The unpaired comparisions are made because certain types of model inadequacies cannot be detected by paired comparison techniques alone. For example, if a models consistent failures on a pairwise basis are only moderate, but there is a strong tendency for a model to predict toward the mean, the model will fail to give sufficient heavy tail, despite relatively good fit in general. Only examination of the full distribution will detect this behavior. The following techniques for unpaired comparisons are used:

i. Cumulative frequency distributions of measured and predicted values are plotted.

j. To study model behavior in simulating the maximum concentrations extreme value distributions developed from the asympotic probability theory as

$$PROB(X \leq X_1) = EXP[-EXP(y)]$$

where $y = (x-u)/a$.

In the above formulation u represents the mode of the extreme value distribution and a represents the Gumbel slope or the scale parameter. The variable y is the reducted variate and x is the maximum concentration in each tracer experiment.

k. The final technique is the Bootstrap analysis which is discussed in the main part of this paper.

TABLE 1. Length scales tested; h is the vehicle height, Wd is the vehicle width, z is height above the surface, and λ_{sp} is the size of the most energic eddy found in wind tunnel velocity measurements (2).

	CASE				
LENGTH SCALE	1	2	3	4	5
λ_x	h	Wd	h	Wd	Wd
λ_y	Wd	Wd	h	Wd	Wd
λ_z	h	h	h	z	λ_{sp}

TABLE 2. Comparision of the results of the five cases.

	CASE1	CASE2	CASE3	CASE4	CASE5
intercept	-0.019	-0.019	-0.025	-0.024	-0.001
slope	0.983	0.981	1.000	0.992	0.921
correlation	0.985	0.985	0.982	0.991	0.979
rms	0.096	0.095	0.105	0.072	0.105
$\sum (O-P)^2$	6.408	6.397	7.447	4.111	11.046

TABLE 3. Comparision between model results in original version(4) and current version for 1157 data points using the GM data.

	ROADWAY 1979	ROADWAY 1984
intercept	0.10	0.05
slope	0.90	1.18
correlation	0.82	0.87
rms error	0.46	0.49

TABLE 4. Comparision of model results using the GM data.

N = 594

	OBSERVED	HIWAY-2	CALINE-3	ROADWAY
Range	.01-4.92	.01-4.68	.09-17.97	.02-5.29
Mean	.96	1.07	.96	1.20
Standard Deviation	.74	.77	1.31	.92
R^2		.70	.29	.65
Slope		.87	.96	1.00
Intercept		.23	.04	.25
Standard Error of Estimate		.42	1.11	.54
Mean of (P/O)		1.30	1.23	1.40
Standard Deviation of (P/O)		.99	1.20	1.02
Mean Difference		.11	.00	.25
Variance		.18	1.23	.29
Average Absolute Error		.30	.41	.41
Root-Mean-Square Error		.44	1.11	.60
Potential Error		1266.9	1995.5	1537.7
Index of Agreement		.91	.64	.86
Mean Fractional Error		-.12	.04	-.21
Unsystematic Mean Square Error (MSE_u)		.18	1.22	.29
Systematic Mean Square Error (MSE_s)		.02	.00	.06
Mean Square Error (MSE)		.20	1.22	.35
MSE_u/MSE		89%	100%	83%
MSE_s/MSE		11%	0%	17%

TABLE 5. Comparision of model predictions with GM data

Data Subset	Model	Percent of predictions within ± 30% of observed concentration	Percent of predictions <30% of the observed concentrations	Precent of predictions >30% of observed concentration
GM Data - Ground level down-wind receptor nearest to raodway where maximum is observed (N=61)	HIWAY-1	40%	7%	53%
	HIWAY-2	75%	17%	8%
	CALINE-3	42%	53%	5%
	ROADWAY	71%	21%	8%
All GM data from all runs (N=594)	HIWAY-1	28%	14%	58%
	HIWAY-2	55%	10%	35%
	CALINE-3	44%	29%	27%
	ROADWAY	46%	13%	41%

TABLE 6. Model comparision of second highest concentration(ppb).

model	mode	Gumbel slope	sample size	predicted$	observed	boot strap 95 % confidence interval
HIWAY-2	1.839	0.6998	61	4.219 ± 1.057	3.770	3.40 - 4.37
CALINE3	1.525	0.7886	60*	4.207 ± 1.191	3.770	3.10 - 4.80
ROADWAY	1.895	0.8143	61	4.665 ± 1.230	3.770	3.56 - 4.69

$ 95% confidence limit to the model predicted second highest concentration based on the extreme value distribution
* one tracer run with very low wind speed is removed from this analysis.

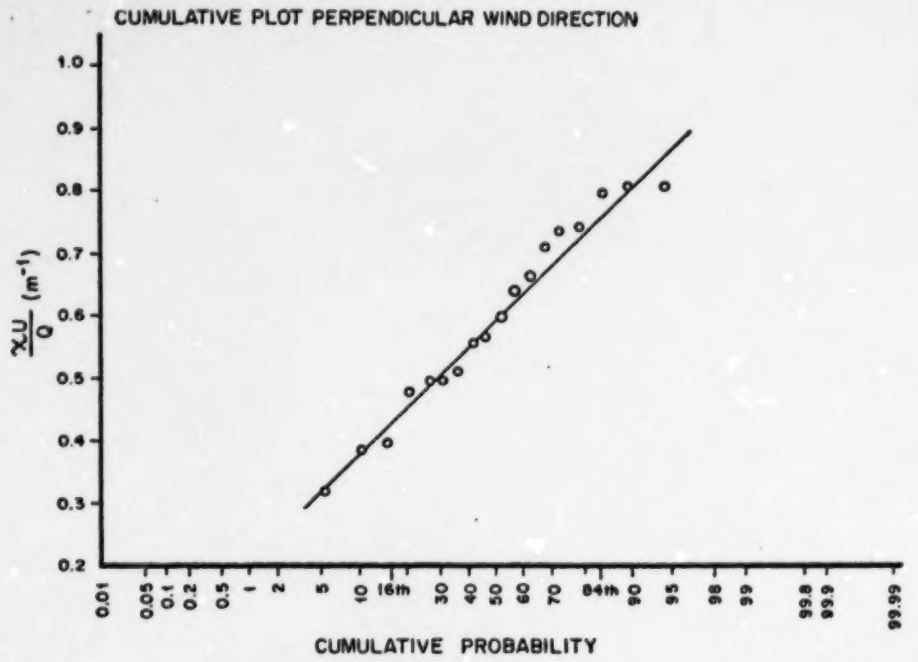

Fig. 1. Cumulative frequency distribution of the normalized concentrations at the nearest roadside recptor under prependicular wind-road orientation.

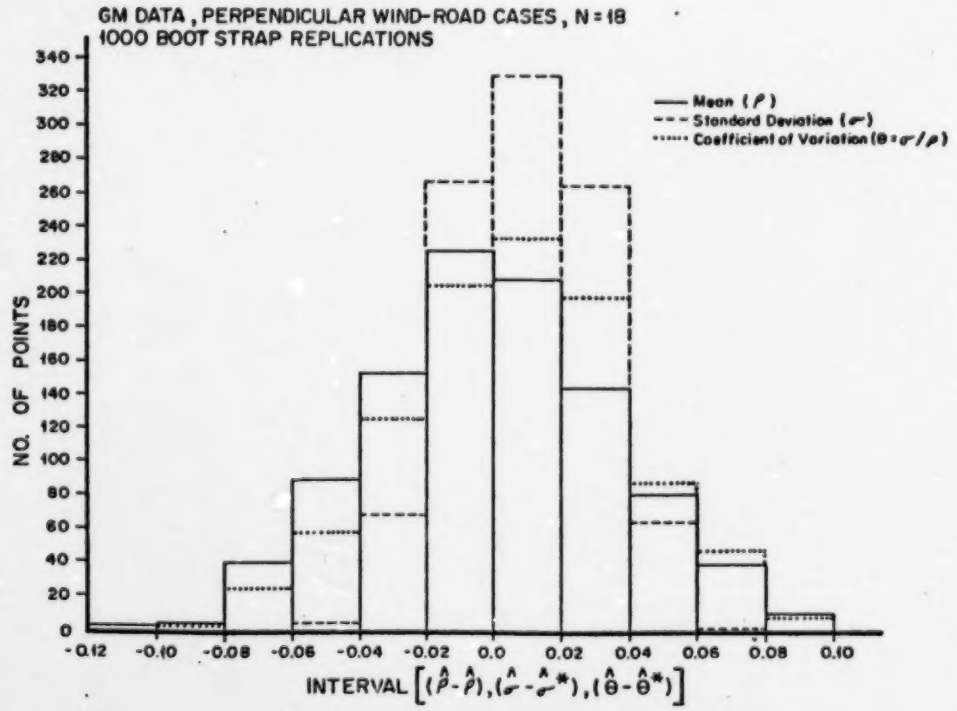

Fig. 2. Uncertainty distribution for the selected parameters using 1000 boot strap replications.

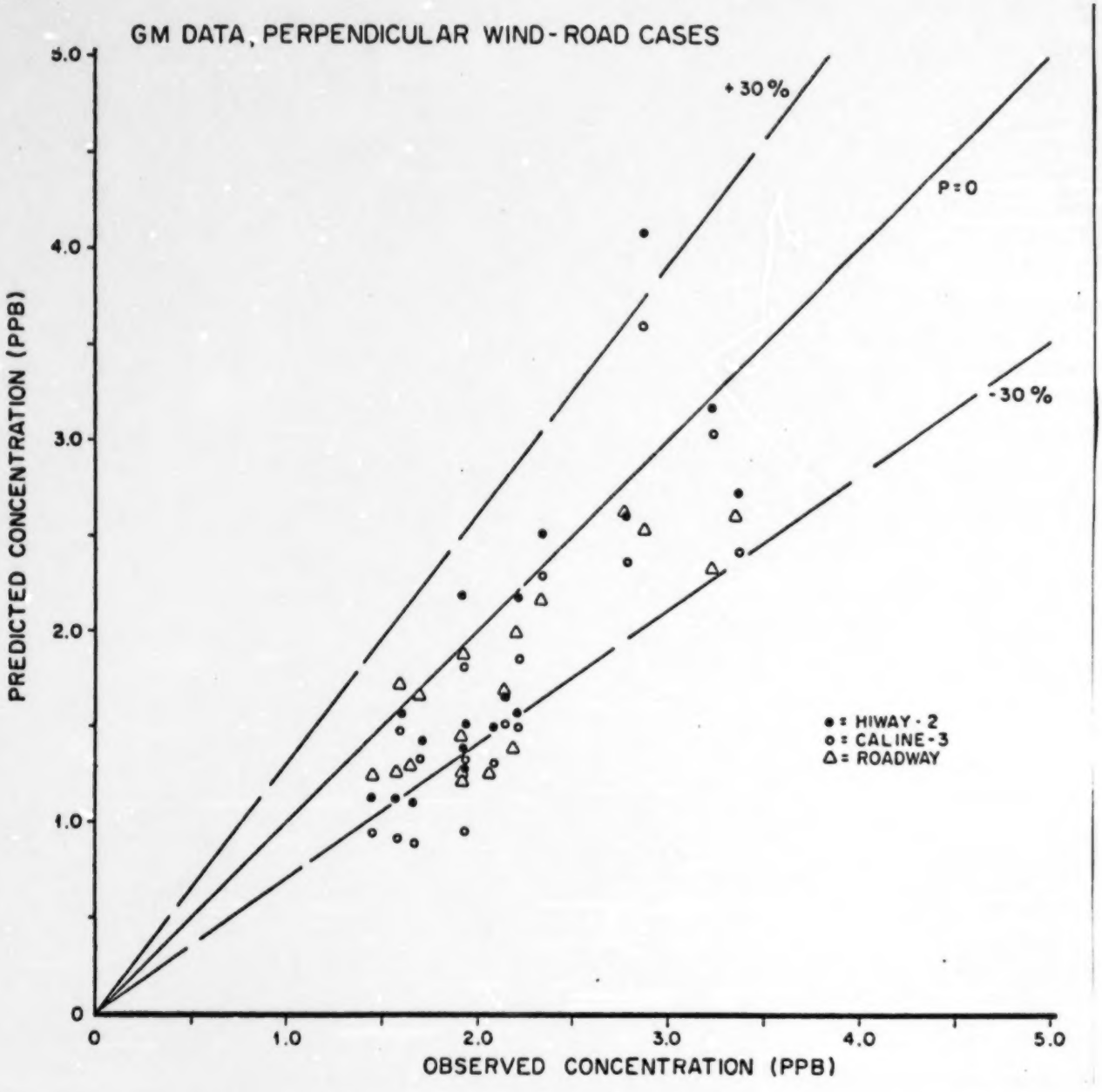

Fig. 3. Scatter plot of model predictions and measurements.

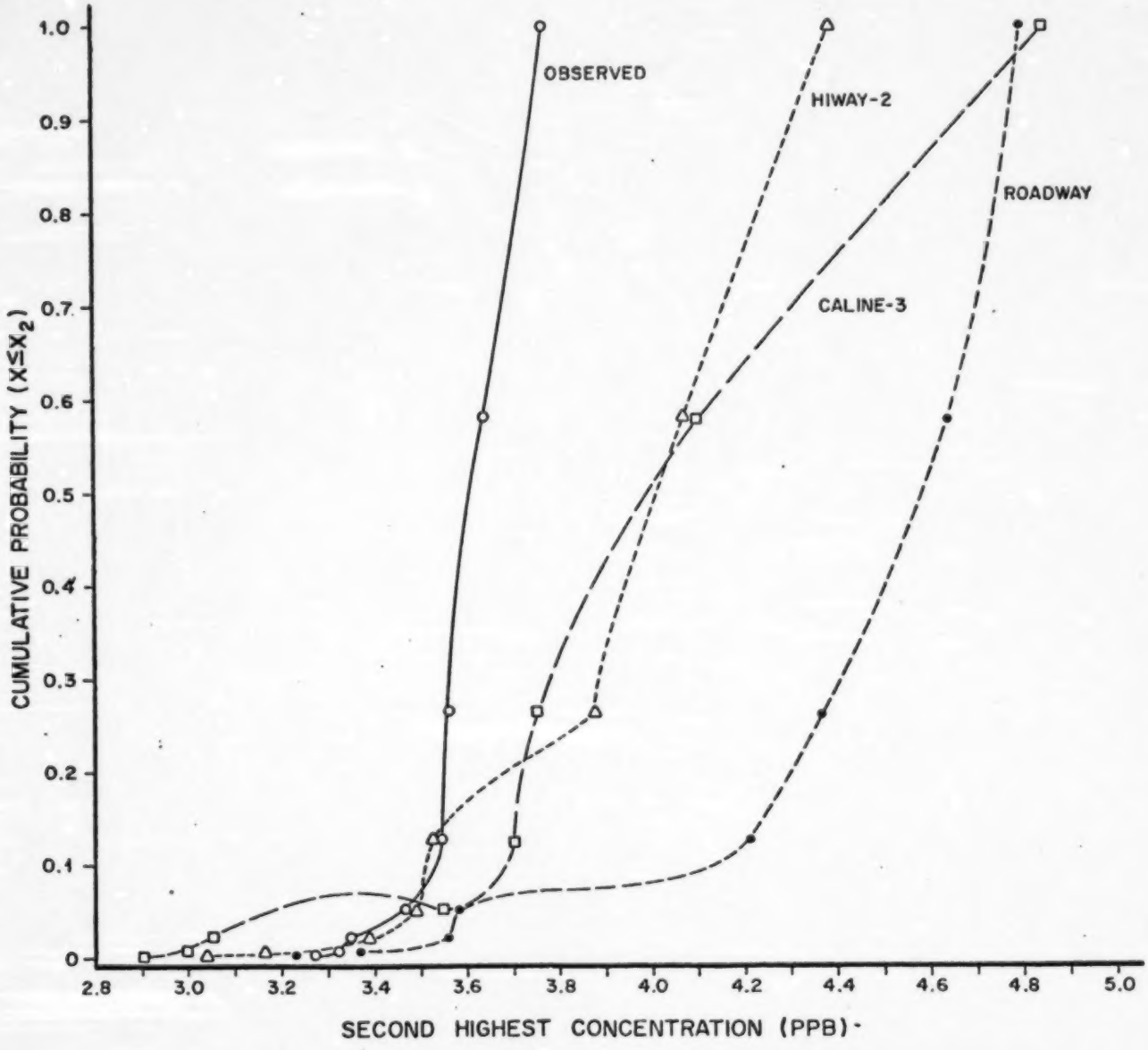

Fig. 4. Cumulative frequency distribution of model-based and monitor-based second highest concentration using 1000 boot strap replications.